Impact of Spatial Scale on Mobility Parameters

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MOTIVATION

- Huge body of work focusing on the understanding of human mobility characteristics [1] utilizing various types of data [2]
- How spatial scale affect the human mobility parameters is still the question?

DATA COLLECTION

FIGURE 1: Ambiciti application (formerly called as SoundCity) monitors the environmental pollution the user is exposed to [3].

DATA PROCESSING

- Perform data cleaning and labeling:
  - Clean by removing data points having location as (0,0) identified in private mode.
  - Associate each data point to arrondissements and cities in France towards spatial scales.
  - Generate paths at three scales using cleaned data. The cleaned dataset has 5629 user with 25,787,201 valid samples collected from 01/07/2015 to 30/09/2017
- Identify PDF for Jump length and Radius of Gyration (R_g) [4].
- Identify best fit using KS test
- Identify KL divergence between distributions identified at different scales.

RESULTS

- Positive lognormal distribution fits best (See Figure 2 and Table 1) both jump length and R_g
- As expected spatial scale affects the distribution parameters
- Other results:
  - Pause time also follow positive lognormal distribution but bias present due to nature of the dataset (crowdsourced dataset) used.
  - Distribution of max and min jump length from users also follow positive lognormal distribution with parameters μ=9.95 σ=2.75 and μ= 3.68 σ= 1.70 respectively at fine grain scale.

CONCLUSION/FUTURE WORK

The findings reported here will be leveraged for revisiting the identified parameters, based on further analysis using complementary datasets.

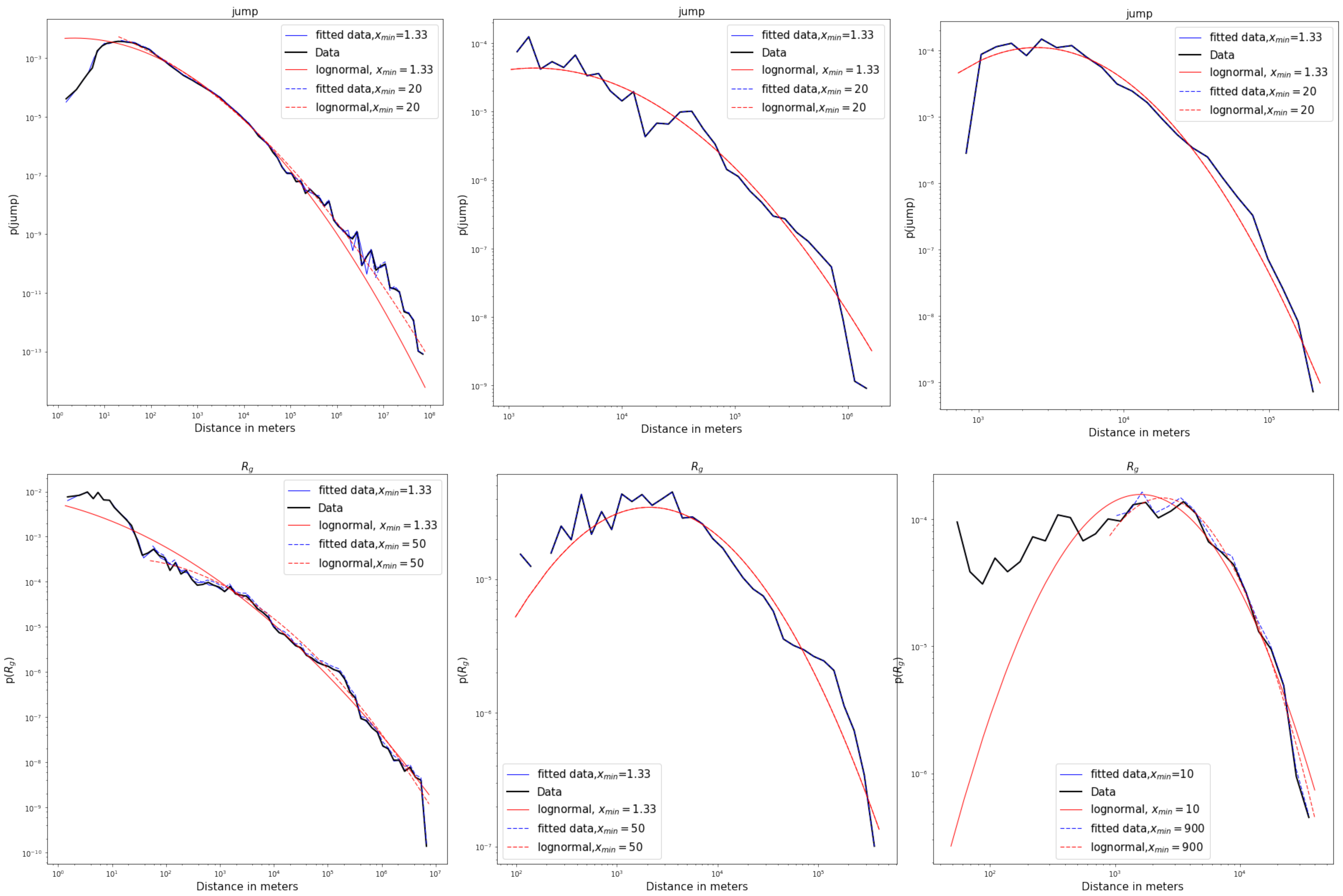

FIGURE 2: Log-Log plot of best fit distribution for jump-length and R_g at different spatial scales with different values of x_{min}. Top row (Jump length): (a) fine grain samples, (b) samples mapped to arrondissements, (c) samples mapped to Ile-de-France cities. Bottom row (R_g): (d) fine grain samples, (e) samples mapped to arrondissements, (f) samples mapped to Ile-de-France cities.

TABLE 1: Distribution fit with identified parameters.

		x_{min} in meters	*power law*		*positive log-normal*			*exponential*		*truncated power law*		
			α	D	μ	σ	D	λ	D	α	β in km	D
Jump length	fine grain	1.33	1.16499	0.32032	6.31135	2.34599	0.04968	0.383×10^{-4}	0.65465	1.00000000047	307	0.18570
		20	1.28349	0.13633	5.67313	2.79791	0.02119	0.366×10^{-4}	0.65156	1.18549609894	760	0.08300
	arrondissements	1.33	1.10381	0.49939	9.917793	1.57635	0.073776	1.550×10^{-5}	0.23363	1.00000000008	823	0.52336
		20	1.14447	0.43674	9.917795	1.57641	0.073770	1.551×10^{-5}	0.23379	1.00000000081	630	0.41185
	cities	10	1.15651	0.51625	8.69207	0.93215	0.056347	1.033×10^{-4}	0.10579	1.0000000011	81	0.55626
		125	1.25882	0.43681	8.69201	0.93232	0.056319	1.045×10^{-4}	0.10689	1.00000000188	53	0.40801
R_g	fine grain	1.33	1.11777	0.30689	8.69591	3.51229	0.06945	5.695×10^{-6}	0.47778	1.00000000733	2430	0.24018
		50	1.17299	0.27522	9.59149	2.61934	0.05053	5.004×10^{-6}	0.43508	1.00000000109	2004	0.16950
	arrondissements	1.33	1.10143	0.46931	10.14405	1.57791	0.076356	1.568×10^{-5}	0.16348	1.00000000649	812	0.51268
		50	1.16046	0.38631	10.14373	1.57844	0.076347	1.571×10^{-5}	0.16376	1.00000004508	557	0.36802
	cities	10	1.16549	0.46070	8.34509	0.98044	0.05847	1.599×10^{-4}	0.08637	1.00000000545	49	0.50714
		900	1.58662	0.25364	8.46224	0.82646	0.02251	1.733×10^{-4}	0.04724	1.00000007368	16	0.19361

TABLE 2: KL divergence between identified distributions at different spatial scale.

		fine grain	arrondissements	cities	x_{min} in meters
Jump length	fine grain	0	4.12646616206	8.14647628506	20
	arrondissements	7.7901952234	0	1.26852900653	20
	cities	1.23656465376	0.502427101463	0	125
R_g	fine grain	0	0.431600843735	4.30231619411	50
	arrondissements	0.210279300944	0	2.74652057699	50
	cities	0.79623349401	0.851536328754	0	900

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